Forecasting and coping with maize yield anomalies through cash transfers in Kenya

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Motivation

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FEWS NET
FAMINE EARLY WARNING SYSTEMS NETWORK

1985

7,7% for DRR[5]
from 1,6 billion US$

830,000[1]
Emergency assistance

2008

+50 %[2]
Maize price

2012

7 % of population[5]
is affected by drought per year

Below average rainfall[3]

2015

Crisis in 2018[4]

2017

4 $ per/capita[5]
spent over the past 20 years

-What is missing to translate Early Warning into Early Action? -

Goals

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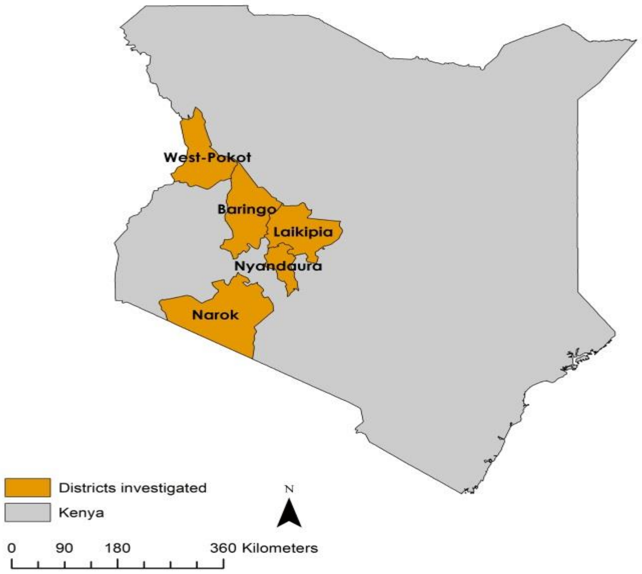
To compare the relative cost-effectiveness of **ex-ante** forecast based cash transfer to small-scale farmers in 5 districts in Kenya compared to **ex-post** cash transfers after harvesting.



Methods | Model Setup

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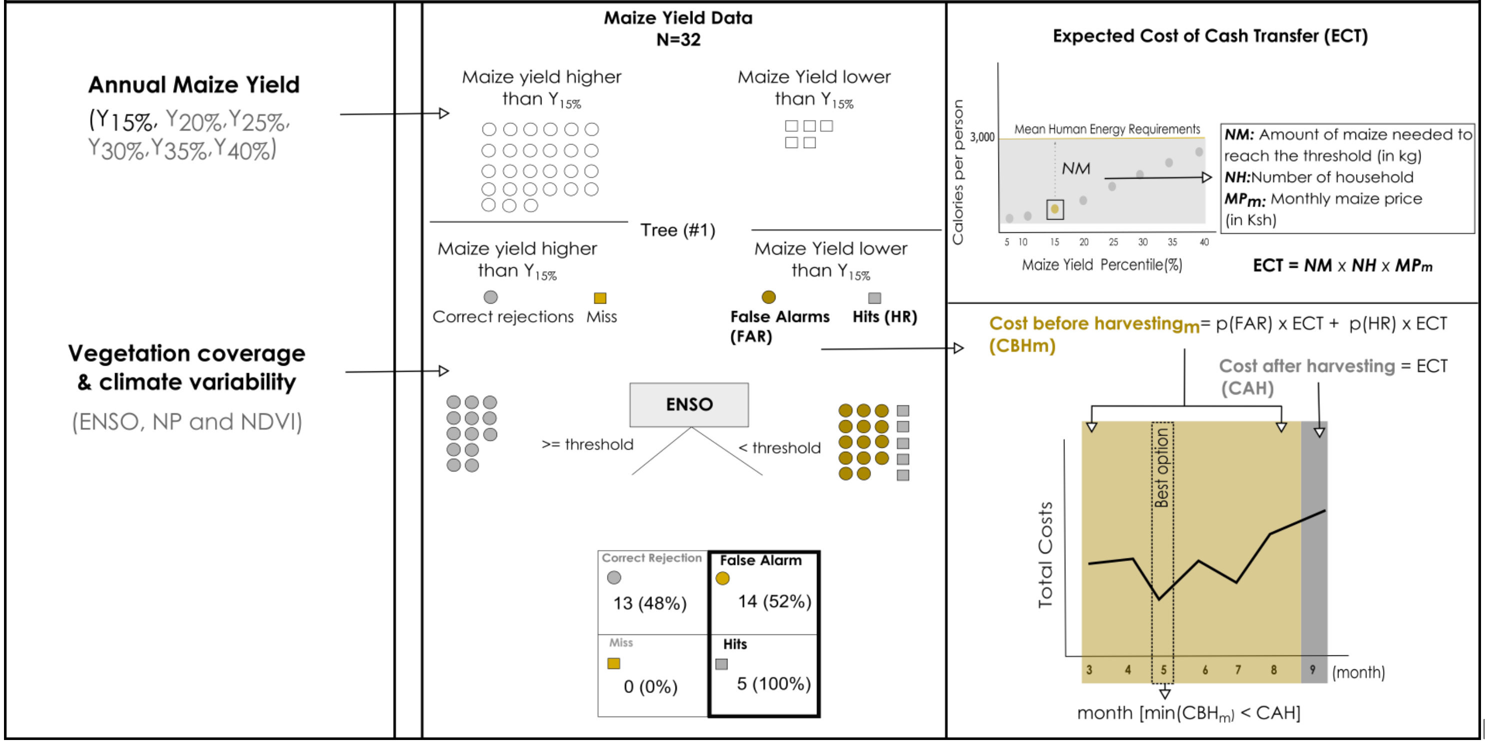
Step 1 | Step 2 | Step 3

Step 1: Extract indicators from datasets between 1983-2014

Step 2: Fit a FFT for a month *m* and obtain probabilities

Step 3: Find the most cost-effective month *m* for disbursing cash transfer



Step 1 | Extract Indicators

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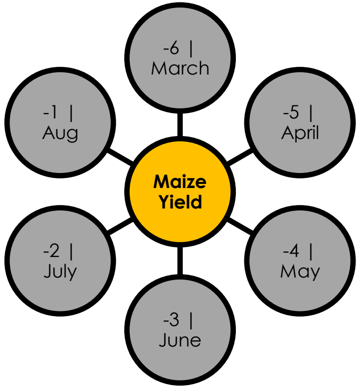
-Datasets-

Index	Reference	Time step
Maize Yield	Kenyan Ministry of Agriculture, Livestock, and Fisheries[6]	Annual
Oceanic Niño Index (ENSO)	National Oceanic and Atmospheric Administration	Monthly
NP (Net Precipitation) ↓ **NP6**	CHIRPS v2.0[7] Hobbins et al. (2016)[8]	Monthly ↓ 6 months accumulated
NDVI ↓ **NDVI6**	NASA GIMMS AVHRR Global NDVI3g.v1[9]	Monthly ↓ 6 months accumulated



-Lead Time-

We extracted two indicators of climate variability: (1) **Net precipitation** (NP), and (2) the **Oceanic Niño Index** (ENSO); and a vegetation coverage indicator: (3) **Normalized difference vegetation index** (NDVI). These three indices were obtained for each month within the maize growing season (from March to August), and the NP and NDVI indices accumulated over different periods ranging from one to six months. These indices were used to predict a range of **low maize yields events**.

Step 1 | Extract Indicators

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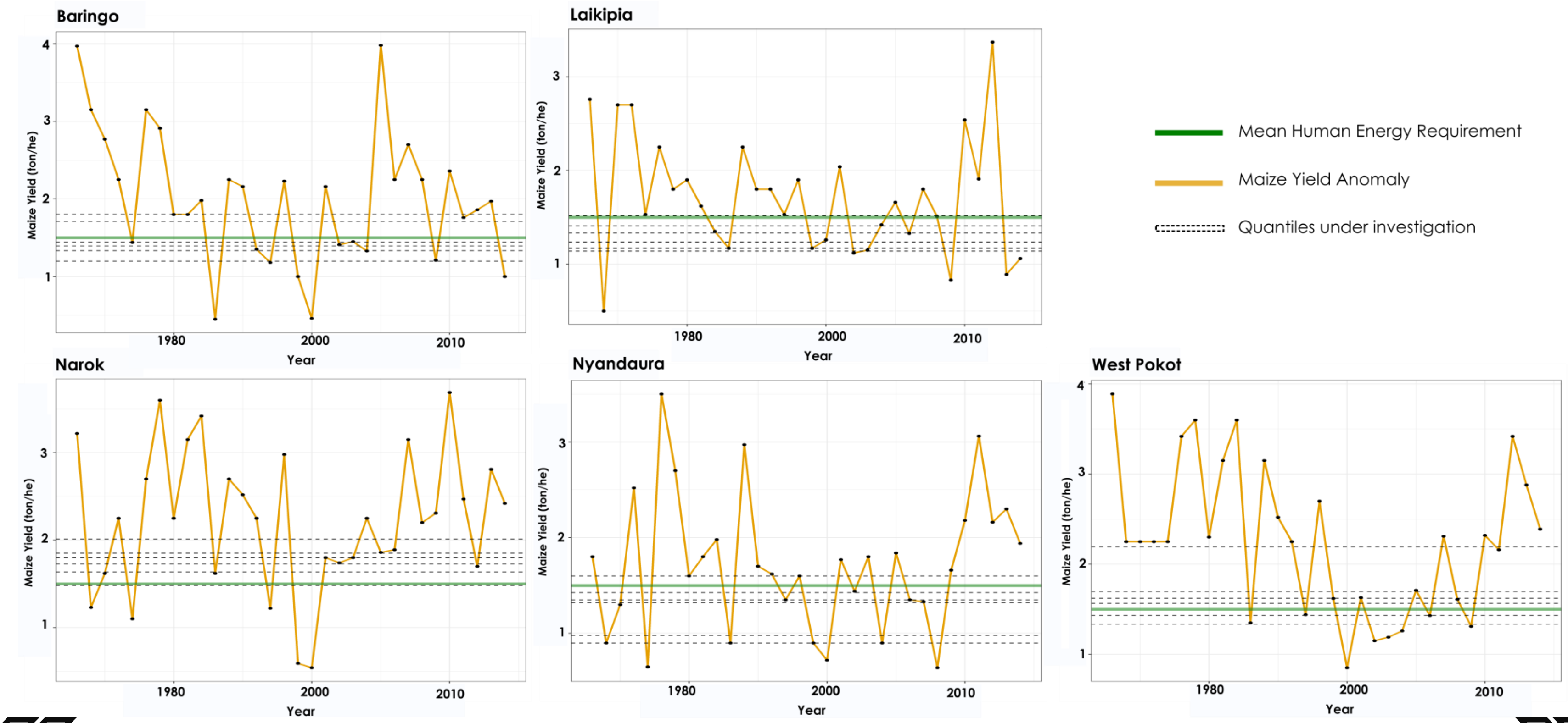
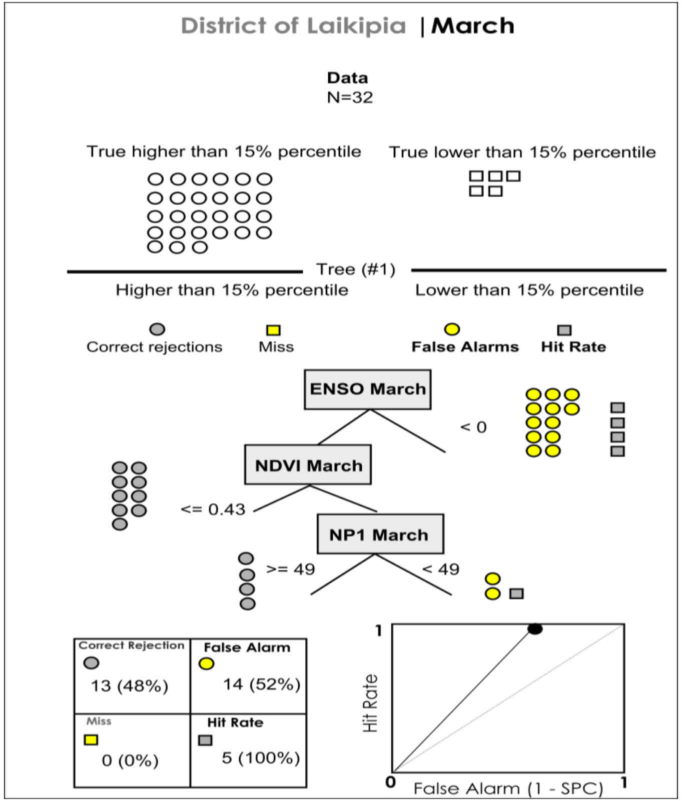


Step 2 | Fit a model

Menu

We used **Fast-and-Frugal Trees** (FFT) to predict low maize yields as a function of indices of climate variability and vegetation coverage (NP, ENSO, NDVI). In heuristic decision-making, FFTs are decision trees for classifying cases (e.g. maize yield) into one of two classes (e.g. low yield vs. high yield) based on particular predictors.

FFT models are simple Machine Learning algorithms that establish rules for making efficient and accurate decisions based on limited information. Such models have the advantage of being easier to interpret, seldom over-fit data, and cognitively simpler to internalise than some other Machine Learning methods.



Step 2 | Obtain probabilities

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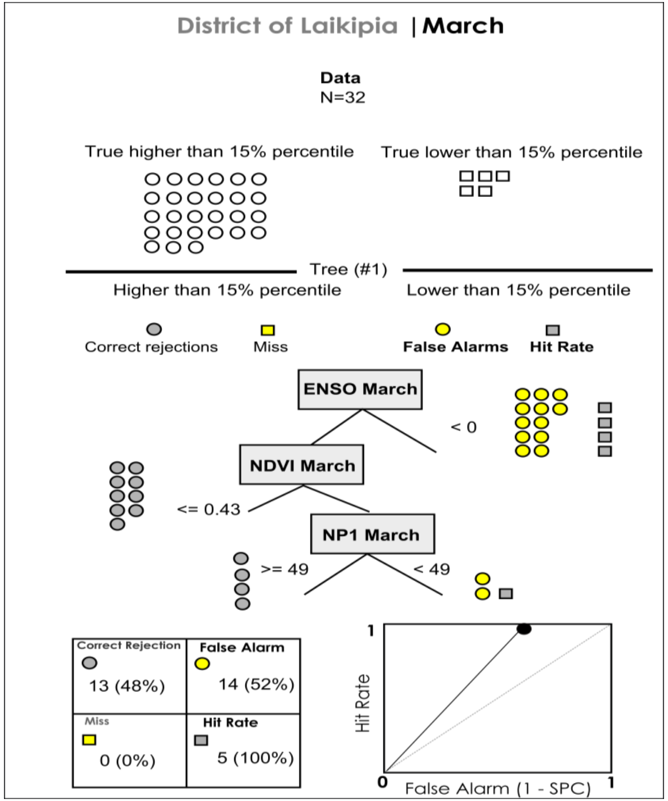
Steps to obtain a FFT model:

1. Ranking and selecting 5 best predictors for each district, low maize yield percentile and month based on their marginal weighted accuracy (WACC). Sensitivity weighting parameter is set to w=0.75, therefore more emphasis is put in identifying low yield cases;
2. Pruning decision trees by cross validating the FFT models using leave-one out cross-validation;
3. Calculation of the ROC index using trapezoidal rule;
4. Performance analysis of the cross-validated FFT model by calculating standard classification statistics such as Hits (HR) and False Alarms (FAR).



Step 3 | Cost-effectiveness

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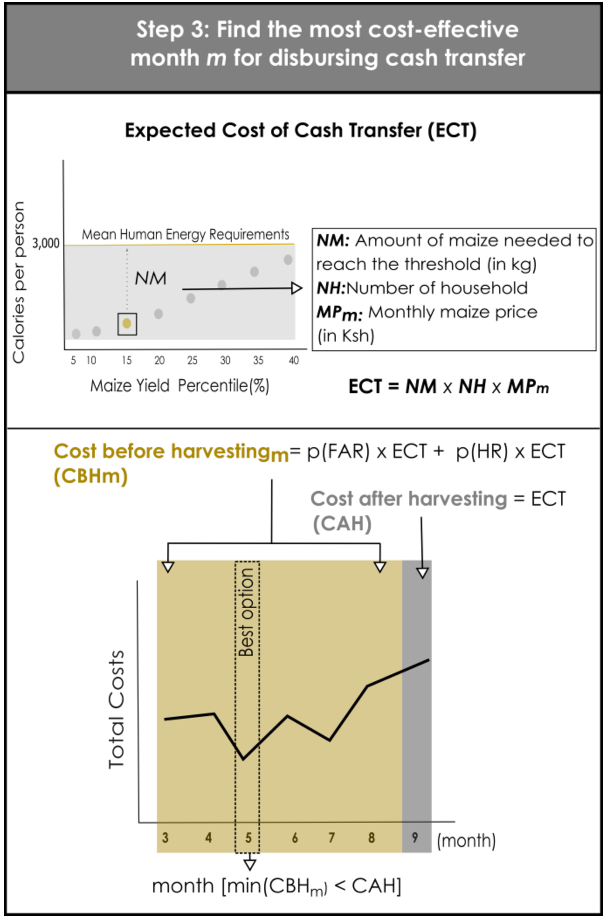
The **overall objective** is to compare the expected costs of early transfer of cash for drought emergency response prompted by expected probabilities of crop yield failures in comparison to post-harvesting cash payments.

The total costs of the cash transfer **(ECT)** mainly depend on the a) total amount of maize per household needed to reach the Human Energy Requirement (HER) mean threshold **(NM)**; b) total number of households, which the chosen early action aims to support **(NH)**; c) and monthly maize price **(MP)**.

Cash transfer is considered to be cost-effective before harvesting in months when CBH < CAH



Step 3 | Cost-effectiveness

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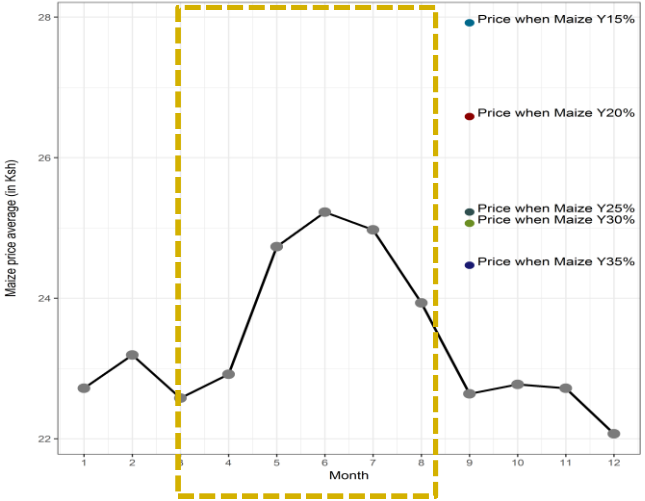
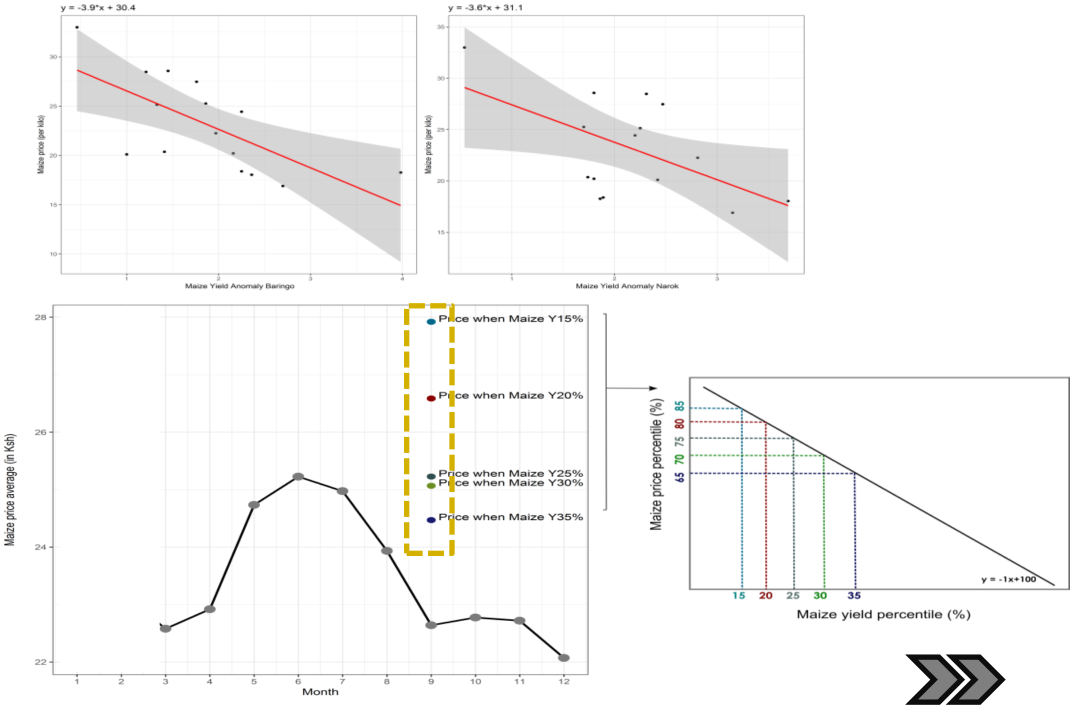
A) Prices before harvesting



B) Prices after harvesting (September)



Results | FFT Models

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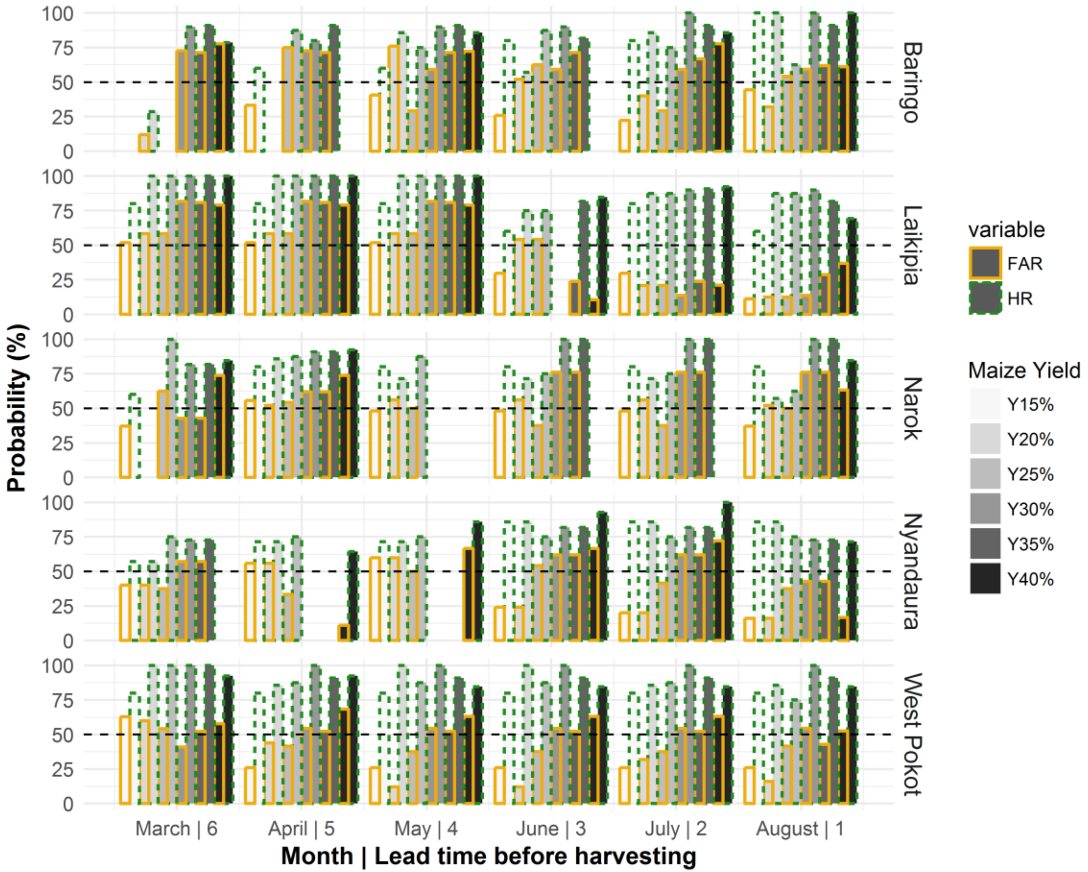

Results 1. Performance of the tested FFT models in predicting true low maize yield events (Hit Rate), and false low maize yield events (False Alarm) per district, maize yield percentile and lead time. Yellow bars represent the False Alarms Rate, and green dashed lines the Hit Rate. Different levels of low maize yield percentiles are highlighted in shades of grey. Dashed black line is drawn at the 50% probability. Sensitivity weighting parameter is w=0.75

Results | Cost-effectiveness assuming perfect forecasts

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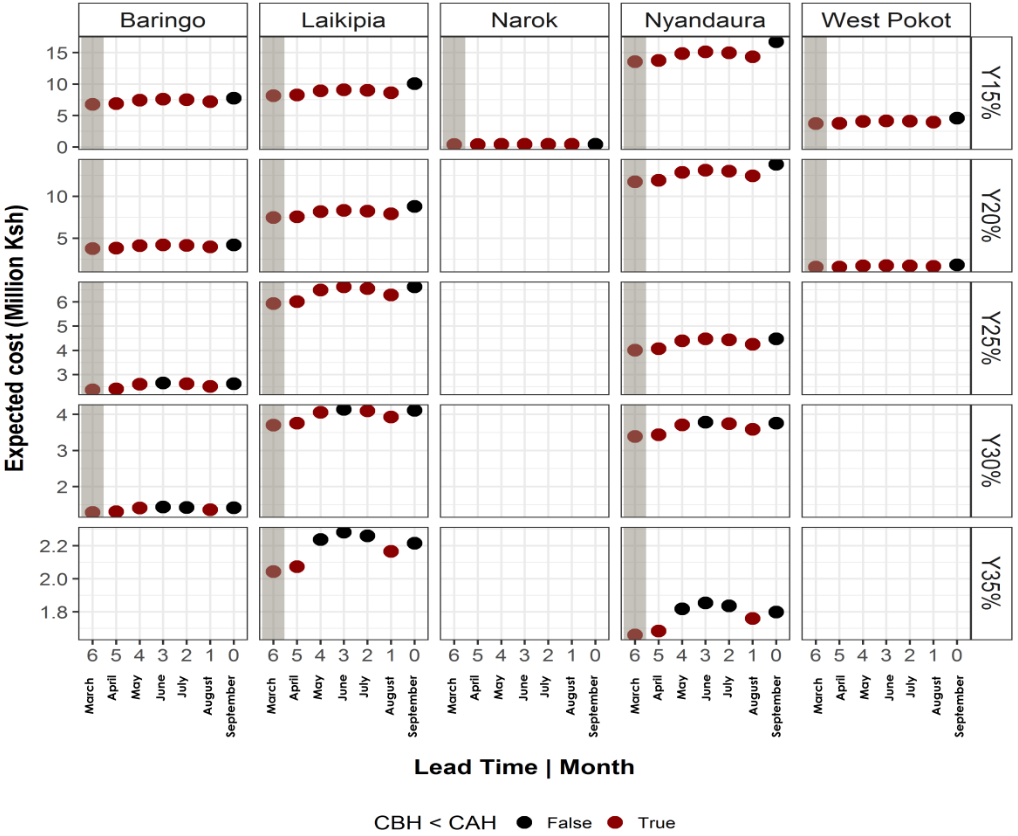

Results 2. Total expected cost of cash transfer per district, lead time and maize yield percentile simulating a perfect forecast before harvesting from March to August (HR=100% and FAR=0%). Dark red dots highlight all lead times before harvesting (starts in September) when expected cost of cash transfer before harvesting is lower than the expected cost of cash transfer after harvesting (CBH_m < CAH), and in black when the opposite. The most cost effective lead time is highlighted in grey. Boxes are blank when the maize yield percentile for the specific district is higher than the mean human energy requirement, therefore, cash transfer is not triggered.

Results | Cost-effectiveness using FFT Models

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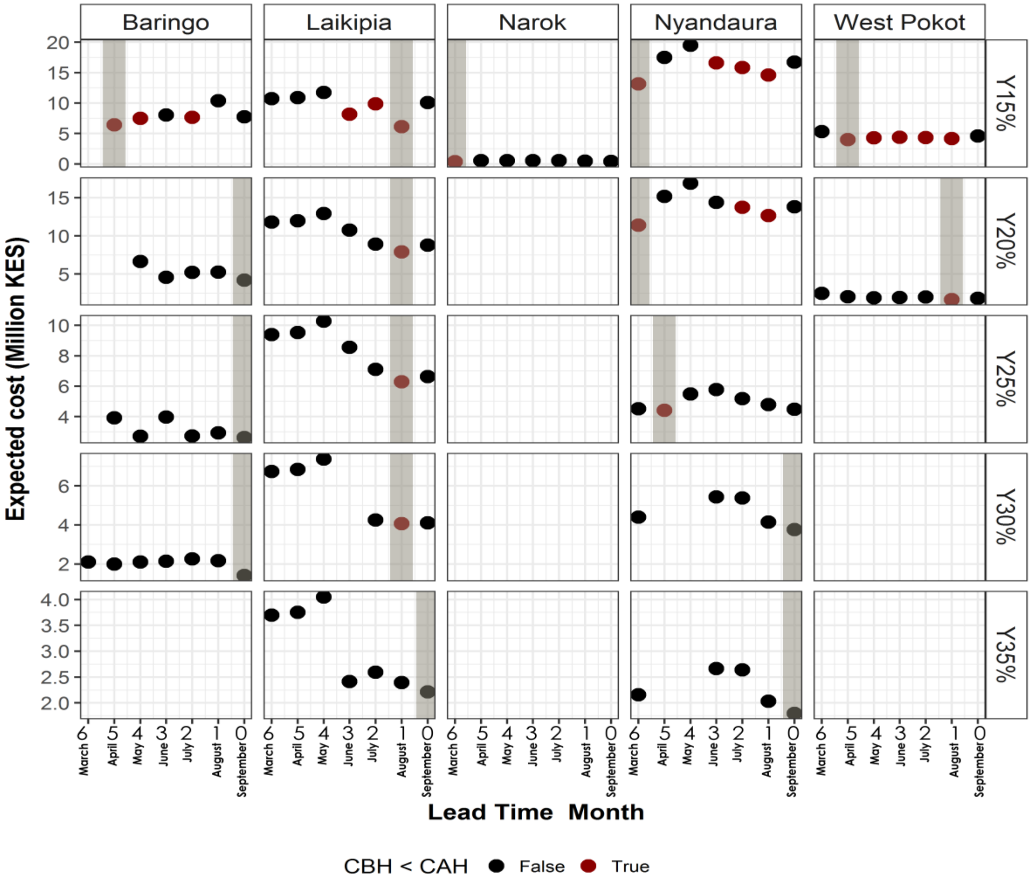

Results 3. Total expected cost of cash transfer per district, lead time and maize yield percentile calculated based on FFT model results (using a weighting parameter of w=0.75). Dark red dots highlight all lead times before harvesting when expected cost of cash transfer before harvesting is lower than the expected cost of cash transfer after harvesting (CBH_m < CAH), and in black when the opposite. The most cost effective lead time is highlighted in grey. Boxes are blank when the maize yield percentile for the specific district is higher than the mean human energy requirement, therefore, cash transfer is not triggered. Results are shown only for lead times and percentile levels, when Hits probability is higher than 50%, and AUC>0.5.

Results | **Sensitivity Analysis**

Click Here

Discussion & Conclusions

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- Overall, FFT models have skill to predicted low maize yields in all five districts, mostly already six months before the start of the harvesting season. FFT models correctly predicted low maize yield cases 85% of the time. Probabilities of False Alarms decrease towards the end of the maize growing season;

- We observed that, when assuming a perfect forecast, cash transfer is expected to be more cost-effective at lead time 6 (March). Cash transfer before the maize harvesting triggered by FFT models forecasts is often more cost-effective than initiating ad hoc emergency cash transfer responses;

- Generating more evidence-based and targeted investment in early actions such as cash transfer is a unique opportunity to ensure that short-term goals of drought risk reductions and food security are met;

- When operationalizing cash transfer, challenges are multiples;

- Currently, the Kenya Hunger Safety Net Programme triggers cash transfers based on a single satellite vegetation condition index (VCI). The National Drought Management Authority could improve the reliability of cash transfers by including other drought early warning indicators such as the ones adopted in this investigation.

Thank you! **Questions? Feedback?**

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References

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[1] FEWS NET (2008). KENYA Food Security Outlook April to September 2008. Retrieved 29 November 2017 from, http://bit.ly/2BuKa8p

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[5] Kellett, Jan, and Alice Caravani. "Financing disaster risk reduction." A 20 year story of international aid (2013).

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[8] Hobbins, M. T., A. Wood, D. J. McEvoy, J. L. Huntington, C. Morton, M. Anderson and C. Hain (2016). "The Evaporative Demand Drought Index. Part I: Linking Drought Evolution to Variations in Evaporative Demand." Journal of Hydrometeorology 17(6): 1745-1761.

[9] Pinzon, Jorge E., and Compton J. Tucker. "A non-stationary 1981–2012 AVHRR NDVI3g time series." *Remote Sensing* 6.8 (2014): 6929-6960.

[10] FEWS NET (2017). Staple Food Price Data. Retrieved 29 November 2017 from, http://www.fews.net/fews-data/337

Sensitivity Analysis | Price

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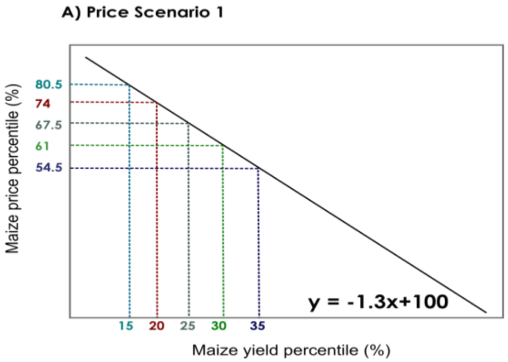
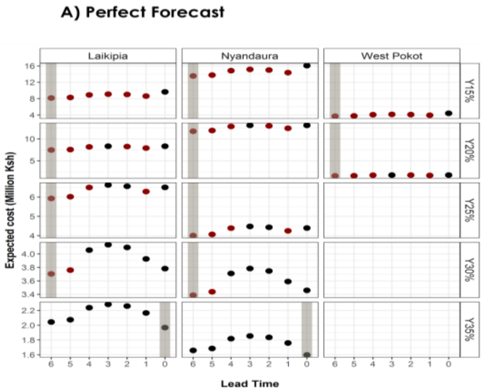
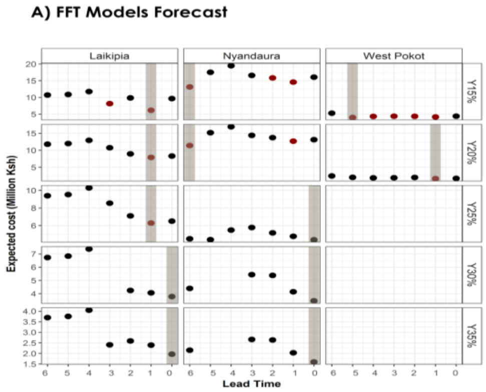
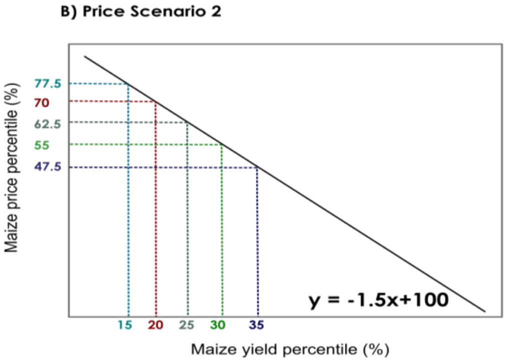
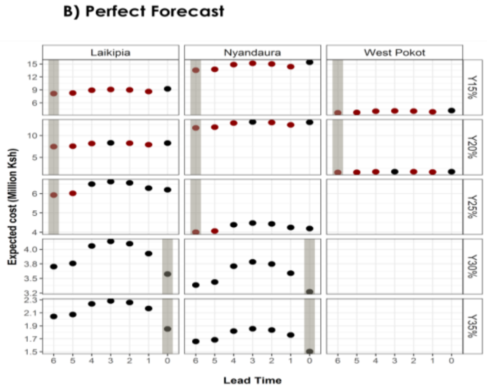


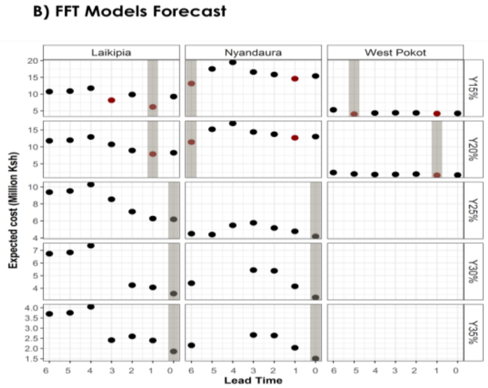




CBH < CAH ● TRUE ● FALSE







CBH < CAH ● TRUE ● FALSE

Sensitivity Analysis | Price

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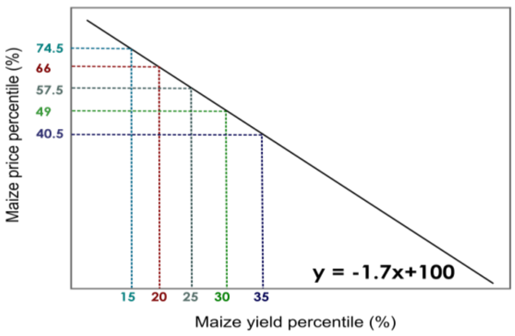
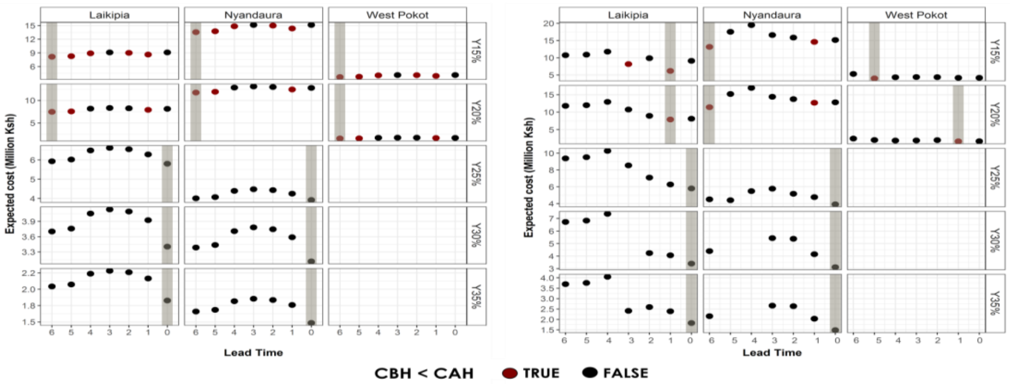
C) Price Scenario 3

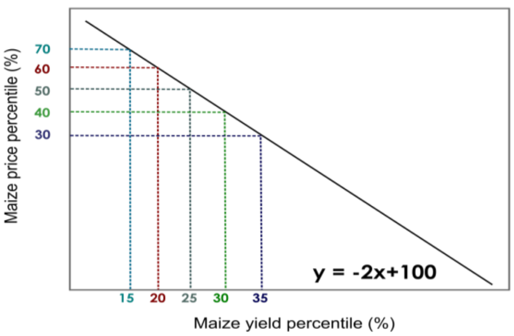


C) Perfect Forecast

C) FFT Models Forecast



D) Price Scenario 4



D) Perfect Forecast

D) FFT Models Forecast